Hybrid BERT + LightGBM Model for Predicting Week of Sale

Introduction:

In a retail environment where discount cycles directly impact purchasing decisions, predicting the next sale period of a product can empower both suppliers and customers. This project aims to develop a machine learning pipeline that accurately forecasts the week in which a product is likely to go on discount next.

The model leverages:

- BERT for contextual text embeddings,
- LightGBM for structured classification

Objective:

The objective is to build a robust hybrid model that:

- Predicts the **number of weeks until the next sale**.
- Uses a **classification approach** (Weeks 1–8 as classes).
- Incorporates both textual and numerical features.
- Provides class-wise performance insights.

Dataset Overview:

- **Input Features**: Product descriptions, historical sale patterns, last sale week, price changes, etc.
- **Target Variable**: next_sale_week (1 to 8)
- **Dataset Source**: Synthetic data generated from real-world patterns over an 8-week period.
- **Size**: ~24,575 samples

Methodology:

- **Text Embedding:**
  - Model: bert-base-uncased
  - Tokenizer: BERT tokenizer
  - Embedding: Mean pooled last hidden layer or [CLS] token output (768-dimensional vector)
- **Classifier:**
  - Model: LGBMClassifier (LightGBM)
  - Hyperparameters: Possibly default or lightly tuned
  - Task: Multi-class classification (8 classes)

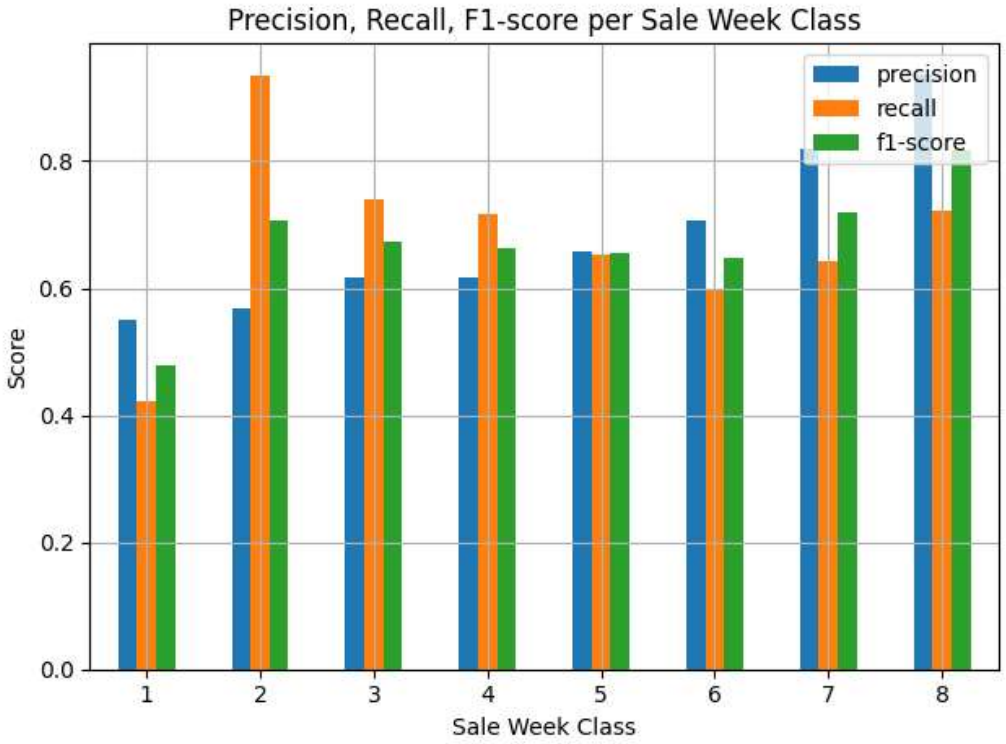
Evaluation Metrics:

Metric	**Value**
Accuracy	0.698
Precision (Macro)	0.684
Recall (Macro)	0.679
F1-Score (Macro)	0.670
Weighted Precision	0.724
Weighted Recall	0.698
Weighted F1-score	0.701
RMSE	1.11 weeks
MAE	0.52 weeks

The macro scores show that performance is slightly affected by class imbalance.

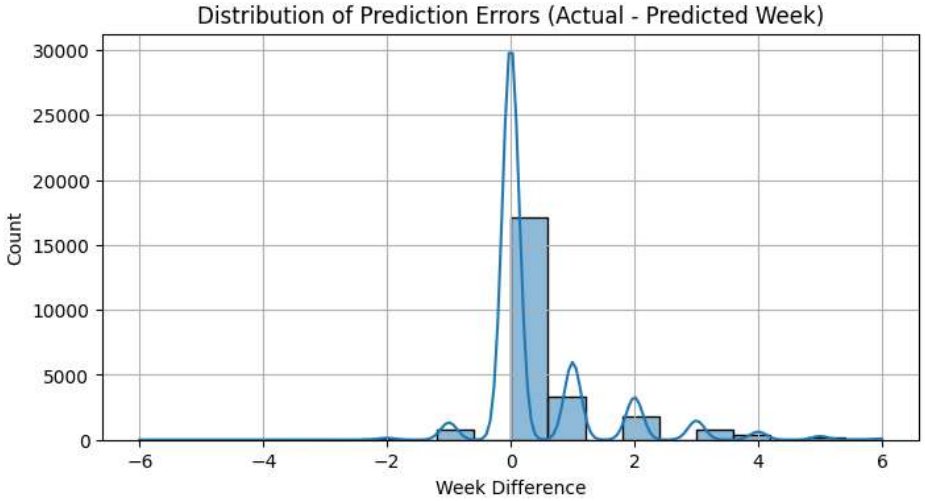
Visual Analysis:

1. **Class-wise Precision, Recall, F1-Score**



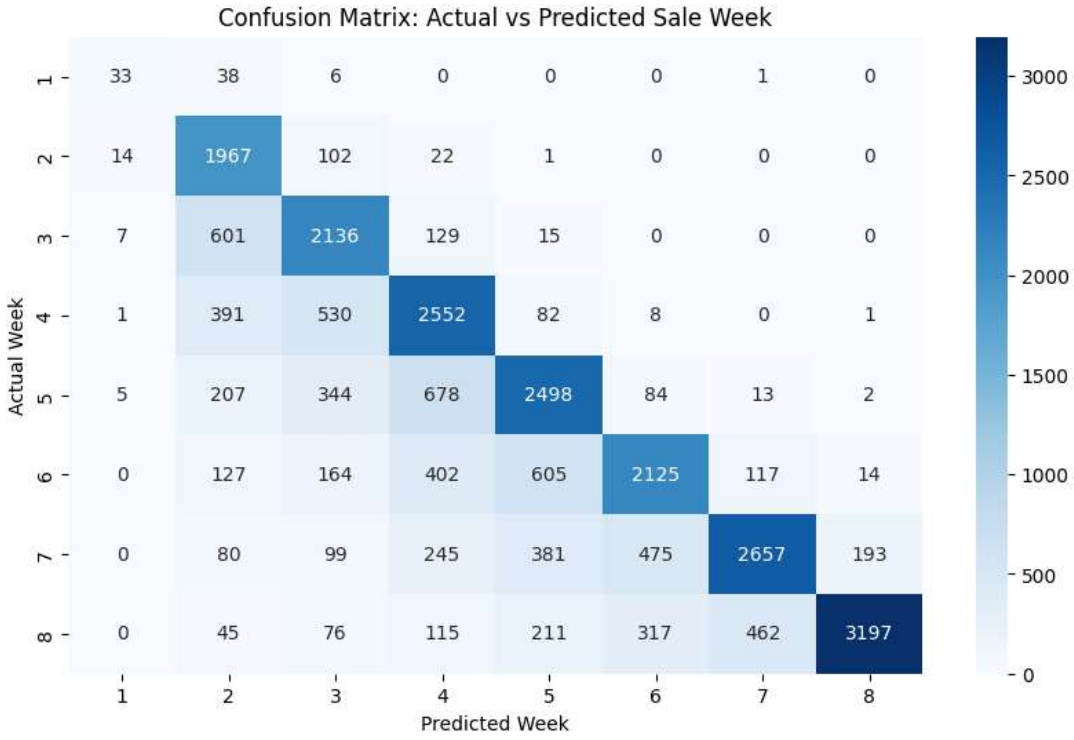
- **Class 8** and **Class 7** show the highest scores.
- **Class 1** has poor performance due to very low support (78 samples).

2. **Prediction Error Distribution:**



- Most predictions are off by **0–1 weeks**, which is acceptable.
- Few large deviations show scope for boundary improvement between adjacent classes.

3. **Confusion Matrix:**



- Diagonal dominance is clear, indicating mostly correct predictions.
- Misclassifications are primarily to **adjacent weeks**, not far-off classes.

Key Findings:

- Model performs **reasonably well** with overall **70% accuracy**.
- **Adjacent week misclassifications** indicate the model understands the sale pattern but struggles with class boundaries.
- High class imbalance (e.g., very few class 1 instances) significantly affects macro metrics.
- Low **RMSE (1.11 weeks)** and **MAE (0.52 weeks)** show prediction is close even if not exact.

Recommendations:

- **Handle Class Imbalance**: Apply techniques like SMOTE, class weights in LightGBM, or oversampling.
- **Hyperparameter Optimization**: Use grid search or Optuna for LightGBM tuning.
- **Feature Engineering**:
  - Add more structured features (e.g., category, brand, frequency).
  - Incorporate historical price patterns.
- **Use Class Grouping**: Merge underrepresented classes or convert to a regression task to reduce sparsity.

- **Alternative Models**: Test with RoBERTa or DistilBERT embeddings, and other classifiers like XGBoost or CatBoost.
- **Temporal Smoothing**: Consider classifying product sale as a week range (e.g., 1–2, 3–4) for real-world tolerance.

Conclusion:

- This hybrid model effectively predicts **the week of sale** using powerful contextual embeddings from BERT and efficient classification from LightGBM. The model performs best when:
  - Predicting common sale weeks (Classes 6–8).
  - Items follow consistent naming patterns.
- The combination proves highly suitable for **retail demand forecasting** or **promotional planning**, especially when interpretability, modularity, and scalability are important.